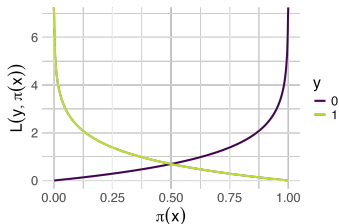


Introduction to Machine Learning

Advanced Risk Minimization

Bernoulli Loss



Learning goals

- Bernoulli (log, logistic, binomial, cross-entropy) loss
- Risk minimizer
- Optimal constant
- Complete separation problem

ON PROBABILITIES

- Likelihood of Bernoulli RV:

$$\mathcal{L}(\theta) = \prod_{i=1}^n \pi(\mathbf{x}^{(i)} | \theta)^{y^{(i)}} (1 - \pi(\mathbf{x}^{(i)} | \theta))^{1-y^{(i)}} \quad y \in \{0, 1\}$$

- Transform into NLL:

$$-\ell(\theta) = \sum_{i=1}^n -y^{(i)} \log(\pi(\mathbf{x}^{(i)} | \theta)) - (1-y^{(i)}) \log(1 - \pi(\mathbf{x}^{(i)} | \theta))$$

- Bernoulli loss: loss on single sample

$$L(y, \pi(\mathbf{x})) = -y \log(\pi(\mathbf{x})) - (1 - y) \log(1 - \pi(\mathbf{x})) \quad y \in \{0, 1\}$$

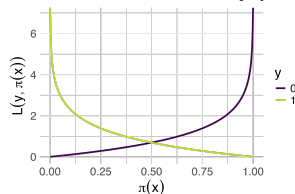


ON PROBABILITIES

- Bernoulli loss

$$L(y, \pi(\mathbf{x})) = -y \log(\pi(\mathbf{x})) - (1 - y) \log(1 - \pi(\mathbf{x})) \quad y \in \{0, 1\}$$

- Confidently wrong predictions are harshly penalized



- A.k.a. Binomial, log, or cross-entropy loss
- Can also write for $y \in \{-1, +1\}$

$$L(y, \pi(\mathbf{x})) = -\frac{1+y}{2} \log(\pi(\mathbf{x})) - \frac{1-y}{2} \log(1-\pi(\mathbf{x})) \quad y \in \{-1, +1\}$$

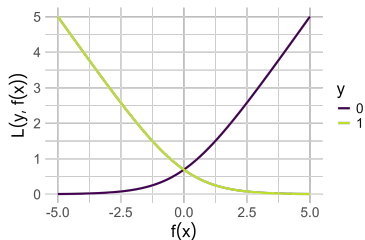
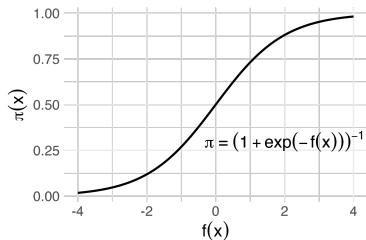


ON DECISION SCORES

- Transform probs into scores (log-odds): $f(\mathbf{x}) = \log\left(\frac{\pi(\mathbf{x})}{1-\pi(\mathbf{x})}\right)$
- Then $\pi(\mathbf{x}) = (1 + \exp(-f(\mathbf{x})))^{-1}$
- Yields equivalent loss formulation

$$L(y, f(\mathbf{x})) = -y \cdot f(\mathbf{x}) + \log(1 + \exp(f(\mathbf{x}))) \quad \text{for } y \in \{0, 1\}$$

- For these and other simple derivations, see deep dive

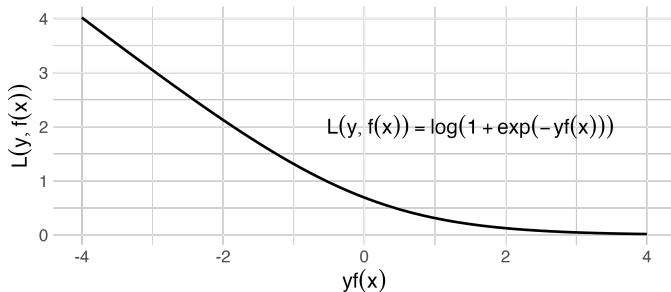


LOSS IN TERMS OF MARGIN

- For $y \in \{-1, +1\}$, loss becomes:

$$L(y, f(\mathbf{x})) = \log(1 + \exp(-y \cdot f(\mathbf{x})))$$

- All loss variants convex, differentiable



RISK MINIMIZER ON PROBS

- For probs and $y \in \{0, 1\}$, the risk minimizer is

$$\pi^*(\tilde{\mathbf{x}}) = \eta(\tilde{\mathbf{x}}) = \mathbb{P}(y = 1 \mid \mathbf{x} = \tilde{\mathbf{x}})$$

Proof: We have seen before

$$\mathcal{R}(f) = \mathbb{E}_{\mathbf{x}} [L(1, \pi(\mathbf{x})) \cdot \eta(\mathbf{x}) + L(0, \pi(\mathbf{x})) \cdot (1 - \eta(\mathbf{x}))]$$

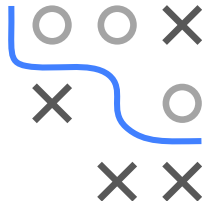
For fixed \mathbf{x} , minimize inner part pointwise, use $c \in (0, 1)$ for best value:

$$\frac{d}{dc} (-\log c \cdot \eta(\mathbf{x}) - \log(1 - c) \cdot (1 - \eta(\mathbf{x}))) = 0$$

$$-\frac{\eta(\mathbf{x})}{c} + \frac{1 - \eta(\mathbf{x})}{1 - c} = 0$$

$$\frac{-\eta(\mathbf{x}) + \eta(\mathbf{x})c + c - \eta(\mathbf{x})c}{c(1 - c)} = 0$$

$$c = \eta(\mathbf{x})$$

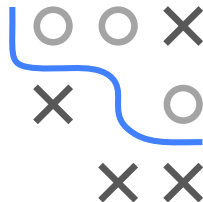
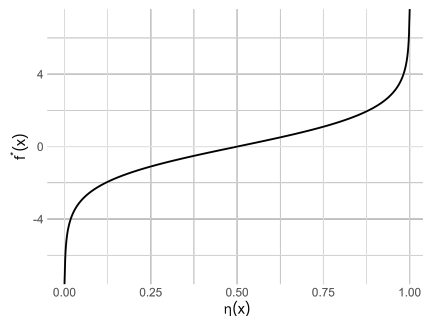


RISK MINIMIZER ON SCORES

- For $y \in \{-1, 1\}$ and scores $f(\mathbf{x})$: RM is pointwise log-odds

$$f^*(\mathbf{x}) = \log\left(\frac{\eta(\mathbf{x})}{1 - \eta(\mathbf{x})}\right)$$

- Undefined for $\eta(\mathbf{x}) \in \{0, 1\}$
- Monotonously increasing in $\eta(\mathbf{x})$, with $f^*(\mathbf{x}) = 0$ if $\eta(\mathbf{x}) = 0.5$



EMPIRICAL OPTIMAL CONSTANT MODELS

- Optimal constant probability model for labels $\mathcal{Y} = \{0, 1\}$ is

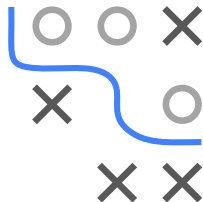
$$\hat{\theta} = \arg \min_{\theta} \mathcal{R}_{\text{emp}}(\theta) = \frac{1}{n} \sum_{i=1}^n y^{(i)}$$

- Fraction of class-1 observations in observed data
- Optimal constant score model:

$$\hat{\theta} = \arg \min_{\theta} \mathcal{R}_{\text{emp}}(\theta) = \log \frac{n_+}{n_-} = \log \frac{n_+/n}{n_-/n}$$

n_- and n_+ are nr. of neg. and pos. observations

- Again shows connection to log-odds



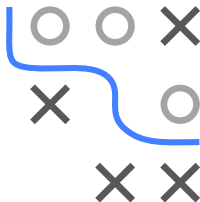
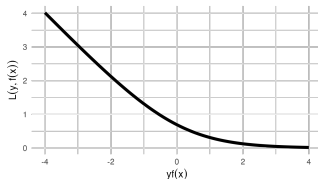
OPTIMIZATION PROPERTIES: CONVERGENCE

- In case of **complete separation**, optimization might fail

- Loss strictly decreasing in margin $y \cdot f(\mathbf{x})$:

$$L(y, f(\mathbf{x})) = \log(1 + \exp(-yf(\mathbf{x})))$$

- f linear in θ , e.g., **log. regr.** with $f(\mathbf{x} | \theta) = \theta^\top \mathbf{x}$



- Assume data separable, so we can find θ :

$$y^{(i)} f(\mathbf{x}^{(i)} | \theta) = y^{(i)} \theta^\top \mathbf{x}^{(i)} > 0 \quad \forall \mathbf{x}^{(i)}$$

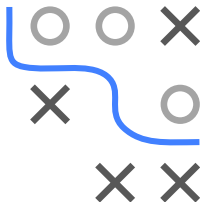
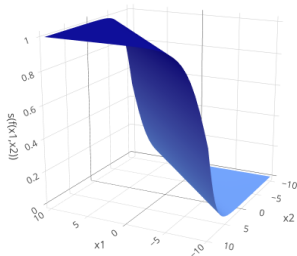
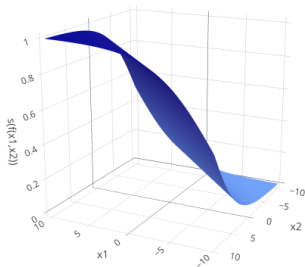
- Can now construct a strictly better θ

$$\mathcal{R}_{\text{emp}}(2 \cdot \theta) = \sum_{i=1}^n L(2y^{(i)} \theta^\top \mathbf{x}^{(i)}) < \mathcal{R}_{\text{emp}}(\theta)$$

- As $\|\theta\|$ increases, sum strictly decreases, as argument of L is strictly larger
- Loss is bounded from below, but no global optimum, cannot converge

OPTIMIZATION PROPERTIES: CONVERGENCE

- Geometrically, this translates to an ever steeper slope of the logistic/softmax function, i.e., increasingly sharp discrimination:



- In practice, data are rarely linearly separable and misclassified examples act as counterweights to increasing parameter values
- Can also use **regularization** for robust solutions